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**BEFORE THE BOARD OF PATENT APPEALS  
AND INTERFERENCES**

Application Number: 09/817,981  
Filing Date: March 27, 2001  
Appellant(s): ALI ET AL.

**MAILED**

**OCT 20 2005**

**Technology Center 2600**

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Russell Gross  
For Appellant

**EXAMINER'S ANSWER**

This is in response to the appeal brief filed 02 May 2005.

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**(1) Real Party in Interest**

A statement identifying by name the real party in interest is contained in the brief.

**(2) Related Appeals and Interferences**

The examiner is not aware of any related appeals, interferences, or judicial proceedings which will directly affect or be directly affected by or have a bearing on the Board's decision in the pending appeal.

**(3) Status of Claims**

The statement of the status of claims contained in the brief is correct

**(4) Status of Amendments After Final**

The appellant's statement of the status of amendments after final rejection contained in the brief is correct.

**(5) Summary of Claimed Subject Matter**

The summary of claimed subject matter contained in the brief is correct

**(6) Grounds of Rejection to be Reviewed on Appeal**

The appellant's statement of the grounds of rejection to be reviewed on appeal is correct.

**(7) Claims Appendix**

The copy of the appealed claims contained in the Appendix to the brief is correct.

**(8) Evidence Relied Upon**

The following is a listing of the evidence relied upon in the rejection of claims under appeal.

- Frisch (WO 00/33207)
- Watanabe et al. (USPN 6,004,015)
- Sims ("Artificial Evolution for Computer Graphics")

**(9) Grounds of Rejection**

The following ground(s) of rejection are applicable to the appealed claims:

- A. Claims 1, 6, 18 and 19 are anticipated by Frisch (WO 00/33207) under 35 USC § 102(a);
- B. Claims 2-5, 7-11, 13-17, and 20-22 are unpatentable under 35 USC § 103(a) over Frisch and Watanabe (USPN 6,004,015); and
- C. Claims 12 and 23 are unpatentable under 35 USC § 103(a) over Frisch and Watanabe and further in view of Sims (Artificial Evolution for Computer Graphics).

These grounds of rejection are provided below.

*Claim Rejections - 35 USC § 102*

1. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless –

(a) the invention was known or used by others in this country, or patented or described in a printed publication in this or a foreign country, before the invention thereof by the applicant for a patent.

2. Claims 1, 6, 18 and 19 are rejected under 35 U.S.C. 102(a) as being anticipated by Frisch (WO 00/33207).

Regarding claim 6—which is representative of claims 1, 18 and 19—Frisch discloses that a gene is a method for enhancing a digital image (i.e. a video processing algorithm) (Frisch pg. 2 lines 19-21).

Frisch further discloses that this gene (i.e. video processing algorithm) comprises control parameters which are optimized using a genetic algorithm (Frisch pg. 13 line 28 – pg. 14 line 7: The determination of a next generation gene parameter as disclosed in Frisch is analogous to the claimed “optimization” of a control parameter.) Consequently, all of the limitations of the claimed “genetic algorithm unit” are disclosed in the Frisch reference.)

The preamble of these claims (1, 6, and 18) are not given patentable weight because they merely recite intended uses and thus do not further limit the claim.

However, even if we assume, *arguendo*, that the preamble limitation of “[A] chain of video processing algorithms for processing a video stream” is given patentable weight, Frisch still anticipates this limitation.

Frisch discloses applying a set of several genes (i.e. algorithms) to a digital image (i.e. a video image) in a predetermined order (Frisch pg. 15 lines 22-29 in conjunction with Figures 12A-21). This is further shown in Frisch at pg. 12 lines 12-24 in conjunction with element 616 of Figure 6: The reference describes that “A genotype is a set of genes ... that are used to alter a digital image in a number of ways.” Thus, this element 616 represents a chain of video processing algorithms. This is consistent with the above analysis that a “gene” is a single video processing algorithm. It logically follows that a set of genes (i.e. a genotype) is a chain of those algorithms.). Accordingly, the limitation of a “chain of video processing algorithms processing a video stream” is disclosed in the Frisch reference.

Specifically referring to claim 1, claim 6 is representative of claim 1 because it recites the same step as claim 1, but in a more limiting manner. The body of these respective claims are as follows:

- Claim 1 recites “[A]n algorithm capable of optimizing said at least one control parameter setting of said at least one video processing algorithm.” (emphasis added)
- Claim 6 recites “[A] genetic algorithm capable of optimizing said at least one control parameter setting of said at least one video processing algorithm.” (emphasis added)

As was discussed above, the Frisch reference discloses a genetic algorithm and thus meets the limitation of the more limiting claim 6. Of course, a genetic algorithm is an algorithm *per se*, so claim 1 is also unquestionably anticipated.

Claims 1 and 18 are substantially similar, and so the same logic applies.

*Claim Rejections - 35 USC § 103*

3. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

(a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negated by the manner in which the invention was made.

4. Claims 2-5, 7-11, 13-17 and 20-22 are rejected under 35 U.S.C. 103(a) as being unpatentable over Frisch as applied to claims 1, 6 and 18-19 above, and further in view of Watanabe et al. (USPN 6,004,015). The arguments as to the relevance of Frisch as applied above are incorporated herein.

Regarding claim 2, which is representative of claim 7, the claim requires an “objective quality metric unit” which is limited solely by the following three functional steps it is capable of performing:

- (a) receiving an output video stream from a chain of video processing algorithms
- (b) determining a fitness value that characterizes the video quality of said output video stream
- (c) providing said fitness value to a genetic algorithm

Regarding limitation (a): Frisch discloses receiving an output video stream from a chain of video processing algorithms (Frisch elements 618 and 622 of Figure 6 and corresponding description (pg. 12 lines 12-24): The reference describes and shows element 618 receiving an output video stream from element 616. Element 616 applies genotypes to a leader image. Frisch discloses that “A genotype is a set of genes ... that are used to alter a digital image in a number of ways.” Thus, this element 616 is a chain of video processing algorithms, just as a “gene” (as previously discussed) is a video enhancement algorithm *per se*.

Regarding limitation (c): Frisch discloses a fitness value that characterizes the video quality of an output video stream (Frisch element 618 of Figure 6). Frisch further discloses providing the fitness value to the genetic algorithm in the genetic algorithm unit (Frisch elements 618 and 622 of Figure 6 in conjunction with pg. 12 lines 12-24: Frisch discloses “receiving” these video output quality based fitness ratings, but does not expressly disclose a unit for “determining” the fitness values.

The only element expressly lacking from the Frisch reference is the limitation from part (b) of determining the fitness value. Since Frisch receives this fitness value (e.g. at element 618 of Figure 6), there exists a colorable argument this feature is inherent in the Frisch reference. Indeed, it would appear that any fitness value that is received, must be determined as well. This argument, however, is unnecessary because the Watanabe reference, in the same genetic algorithm image processing environment, expressly discloses this determination and explicitly provides a motivation that one of ordinary skill in the art could use to make a better system.

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Watanabe discloses a unit for determining fitness values (Watanabe col. 22 lines 31-38 in conjunction with element 105 of Figure 1: The reference expressly describes a fitness calculation section for calculating a fitness).

It would have been obvious to one reasonably skilled in the art at the time of the invention to modify Frisch's video processing system—which receives the fitness value directly from the user—by dedicating a unit for determining the fitness value without user intervention as taught by Watanabe. Such a modification would have allowed for a system that automated the determination of fitness values and thereby reduced the user's burden (Watanabe col. 5 lines 41-50).

With regard to claim 8, which is representative of claims 3 and 20, Frisch further discloses using a fitness value to optimize a control parameter setting (Frisch, elements 622 and 624 of Figure 6).

With regard to claim 9, which is representative of claims 4 and 21, Frisch further discloses a genetic algorithm capable of optimizing a plurality of control parameter settings in a chain of video processing algorithms (Frisch, Figure 6). Figure 6 of Frisch shows the optimization of a genotype. A genotype as disclosed in Frisch comprises a plurality of genes, which comprise a plurality of parameters. The genes as disclosed in Frisch are analogous to video processing algorithms as recited in the claim. It follows that a genotype as disclosed in Frisch is analogous to a chain of video processing algorithms as recited in the claim. As a result, optimizing a genotype as disclosed in Frisch is analogous to optimizing a plurality of control parameter settings of each of a plurality of video processing algorithms in a chain of video processing algorithms as recited in the claim.

With regard to claim 10, which is representative of claim 5, the further limitations of the claim have been addressed in the above arguments with respect to claims 2 and 7.

With regard to claim 11, which is representative of claim 22, the further limitations of the claim have been addressed in the above arguments with respect to claims 3, 8 and 20.

With regard to claim 13, which is representative of claim 24, Frisch further discloses a peaking parameter (Frisch Figure 17). The contrast parameter disclosed in Frisch is analogous to the peaking parameter as recited in the claim.

With regard to claim 15, Frisch further discloses that candidate solutions that will not provide an improvement in video quality are excluded (Frisch, Figure 6). The images which do not have the highest fitness rating are excluded. These images are analogous to the candidate solutions that will not provide an improvement in video quality.

With regard to claim 16, Frisch further discloses that a limited number of representative candidate solutions likely to provide an improvement in video quality are considered (Frisch, Figure 6). Only the candidate solutions with the highest fitness ratings are considered.

With regard to claim 17, Frisch further discloses deriving candidate solutions from previously existing desirable candidate solutions (Frisch, element 622 of Figure 6).

With regard to claim 14, all of the limitations of the claim have been addressed in the above arguments with respect to claim 11.

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5. Claims 12 and 23 are rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Frisch and Watanabe as applied to claims 11 and 22 above, and further in view of Sims ("Artificial Evolution for Computer Graphics"). The arguments as to the relevance of the combination of Frisch and Watanabe as applied above are incorporated herein.

With regard to claim 12, which is representative of claim 23, the combination of Frisch and Watanabe fails to expressly disclose the order of the application of the algorithms as a control parameter setting. Sims, however, discloses that the order of the applications changes during mutations (Sims page 9 section 4.2). These different mutations (with differently ordered algorithms) are then evaluated for fitness. As a result, the order of the functions as disclosed in Sims is analogous to a control parameter setting as recited in the claim.

It would have been obvious to one reasonably skilled in the art at the time of the invention to modify Frisch and Watanabe's video processing system to include the order of the application of the video processing algorithms as a control parameter setting as taught by Sims. Such a modification would have allowed for a system with improved quality of output video stream by utilizing an additional parameter (Sims pg. 9 section 4.2).

#### (10) Response to Argument

(a) Regarding the 102 rejection of claim 1, appellant alleges that Frisch fails to disclose an optimization unit capable of optimizing at least one control parameter setting. Specifically, appellant argues that:

*"rather than teaching an optimizing unit capable of optimizing at least one control parameter, Frisch teaches a user-subjective trial and error method for determining a relative measure, i.e., fitness value for each of child images and uses a weighted average between the lead image and the child image associated with the highest fitness value to evolve the lead image as a next generation image." (see appeal brief, pg. 7).*

#### *(Examiner's response)*

The claim requires an "optimization." Appellant has failed to point to any language in the claims or the specification that might show that Frisch's image optimization does not qualify as the claimed "optimization."

Frisch discloses that a "gene" defines a method for enhancing an image (i.e. a gene is an image enhancement algorithm). A gene contains parameters, which are used to compute "next generation gene parameters." These "next generation gene parameters" are computed by performing a weighted average of the leader gene parameter and the child gene parameter. Frisch's computation is thus analogous to the optimization of a control parameter setting because the parameters are being optimized by determining the next gene parameter. This is how genetic algorithms work.

Appellant's argument that Frisch's "optimization" is subjective and therefore does not meet the claim limitations is not pertinent to the claimed subject matter. The claim simply requires an optimization. Frisch quite clearly performs such an optimization.

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(b) Regarding the 103 rejection over Frisch and Watanabe to dependent claim 2, appellant alleges the following: “Frisch fails to teach or suggest obtaining a child image fitness value suitable for optimizing the digital image as recited in claim 1, from which claim 2 depends.” (see appeal brief, pg. 9)

*(Examiner's response)*

Claim 1 does not contain such a limitation. Appellant's statement that this limitation is “recited in claim 1” is erroneous.

(c) On pages 10-11 of the brief, under the heading “No Motivation Exists for the Examiner's Proposed Modification,” appellant argues that neither Frisch nor Watanabe disclose an “objective quality metric unit.” Rather than directing arguments to the motivation expressly provided in the final rejection, appellant merely alleges that the aforesaid limitation is lacking in both references.

*(Examiner's response)*

The term “objective quality metric unit” is not expressly defined in the specification and is thus limited by the steps recited in the claim that it is capable of performing.

Claim 2 recites “[an] objective quality metric unit” capable of performing the following 3 steps:

1. receiving an output video stream from [a] chain of video processing algorithms
2. determining a fitness value that characterizes the video quality of said output video stream
3. capable of providing said fitness value to said algorithm in [the] optimization unit

The “objective quality metric unit” is defined by above three steps, not by a given identifier. The term “objective quality metric unit” does not further limit the claim, but merely provides a label for a “unit” which is limited solely by steps it is capable of performing. Frisch and Watanabe disclose these steps and appellant has advanced no arguments to the contrary. Accordingly, the cited combination teaches an “objective quality metric unit.”

However, even if we assume, *arguendo*, that this phrase does further limit the claim, the “objective” aspect is met by the Watanabe reference. The passage cited from Watanabe describes that the fitness is calculated on the basis of an evaluation value calculated using a “prescribed fitness function.” (Watanabe col. 22 lines 31-37). In fact, appellant admits in the brief that “[T]he combined device would *dynamically determine* fitness values and ... remove the burden from the user to determine a fitness value.” (pg. 13 -- emphasis added). With this admission, appellant aptly states that the cited combination determines fitness values without user subjectivity.

Regarding motivation to combine references, appellant has advanced no arguments to dispute the provided motivation. The contrary, appellant's later statements, on the first paragraph of pg. 13 of the brief, are an admission that the motivation to combine references is valid (“[T]he combined device would dynamically determine fitness values and merely remove the burden from the user to determine a fitness value”). This statement echoes the motivation to combine references cited by the examiner and found expressly stated in the Watanabe reference.



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(d) On pages 12-13 of the brief, under the heading “Examiner’s Proposed Modification of Frisch Fails to Arrive at the Present Invention,” appellant repeats the arguments stated in part (c) above.

*(Examiner’s response)*

Please see the response to part (c) above.

(e) On pages 13-14 of the brief, appellant argues that the rejection to claims 12 and 23 in view of Frisch, Watanabe and Sims is improper. Specifically, appellant alleges that “Sims is silent on a system for optimizing at least one control parameter setting.”

*(Examiner’s response)*

This argument is unpersuasive. The Sims reference was brought in to meet the limitation of the order of the application of the algorithms as a control parameter setting. The final rejection explains how Sims meets this limitation and how these references are combinable. Appellant has advanced no argument to the contrary.

**(11) Related Proceeding(s) Appendix**

No decision rendered by a court or the board is identified by the examiner in the Related Appeals and Interferences section of this examiner’s answer.

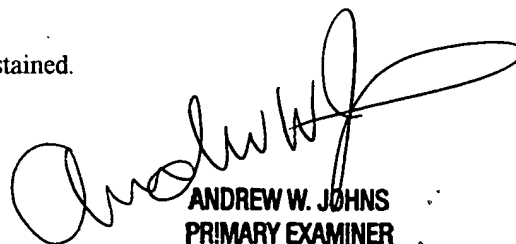
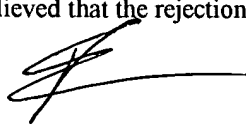
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*Conclusion*

For the above reasons, it is believed that the rejections should be sustained.

Respectfully submitted,

Patrick L. Edwards



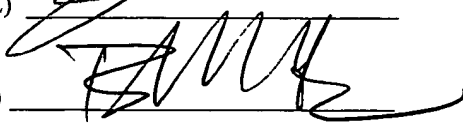
**ANDREW W. JOHNS**  
**PRIMARY EXAMINER**

conferees:

Joseph Mancuso (SPE)



Bhavesh Mehta (SPE)



# Artificial Evolution for Computer Graphics

Karl Sims

Thinking Machines Corporation

## 1 ABSTRACT

This paper describes how evolutionary techniques of variation and selection can be used to create complex simulated structures, textures, and motions for use in computer graphics and animation. Interactive selection, based on visual perception of procedurally generated results, allows the user to direct simulated evolutions in preferred directions. Several examples using these methods have been implemented and are described. 3D plant structures are grown using fixed sets of genetic parameters. Images, solid textures, and animations are created using mutating symbolic lisp expressions. Genotypes consisting of symbolic expressions are presented as an attempt to surpass the limitations of fixed-length genotypes with predefined expression rules. It is proposed that artificial evolution has potential as a powerful tool for achieving flexible complexity with a minimum of user input and knowledge of details.

## 2 INTRODUCTION

Procedural models are increasingly employed in computer graphics to create scenes and animations having high degrees of complexity. A price paid for this complexity is that the user often loses the ability to maintain sufficient control over the results. Procedural models can also have limitations because the details of the procedure must be conceived, understood, and designed by a human. The techniques presented here contribute towards solutions to these problems by enabling "evolution" of procedural models using interactive "perceptual selection." Although they do not give complete control over every detail of the results, they do permit the creation of a large variety of complex entities which are still user directed, and the user is not required to understand the underlying creation process involved.

Many years ago Charles Darwin proposed the theory that all species came about via the process of evolution [2]. Evolution is now considered not only powerful enough to bring about biological entities as complex as humans and consciousness, but also useful in simulation to create algorithms and structures of higher levels of complexity than could easily be built by design. Genetic algorithms have shown to be a useful method of searching large spaces using simulated systems of variation and selection [23][7][6][5]. In *The Blind Watchmaker*, Dawkins has demonstrated the power of Darwinism with a simulated evolution of 2D branching structures made from sets of genetic parameters. The user selects the "biomorphs" that survive and reproduce to create each new generation [4][3]. Latham and Todd have applied these concepts to help generate computer sculptures made with constructive solid geometry techniques [28][9].

Variations on these techniques are used here with the emphasis on the potential of creating forms, textures, and motions that are useful in the production of computer graphics and animation, and also on the potential of using representations that are not bounded by a fixed space of possible results.

### 2.1 Evolution

Both biological and simulated evolutions involve the basic concepts of genotype and phenotype, and the processes of expression, selection, and reproduction with variation.

The *genotype* is the genetic information that codes for the creation of an individual. In biological systems, genotypes are normally composed of DNA. In simulated evolutions there are many possible representations of genotypes, such as strings of binary digits, sets of procedural parameters, or symbolic expressions. The *phenotype* is the individual itself, or the form that results from the developmental rules and the genotype. *Expression* is the process by which the phenotype is generated from the genotype. For example, expression can be a biological developmental process that

reads and executes the information from DNA strands, or a set of procedural rules that utilize a set of genetic parameters to create a simulated structure. Usually, there is a significant amplification of information between the genotype and phenotype.

*Selection* is the process by which the fitness of phenotypes is determined. The likelihood of survival and the number of new offspring an individual generates is proportional to its fitness measure. *Fitness* is simply the ability of an organism to survive and reproduce. In simulation, it can be calculated by an explicitly defined fitness evaluation function, or it can be provided by a human observer as it is in this work.

*Reproduction* is the process by which new genotypes are generated from an existing genotype or genotypes. For evolution to progress there must be *variation* or mutations in new genotypes with some frequency. Mutations are usually probabilistic as opposed to deterministic. Note that selection is, in general, non-random and is performed on phenotypes; variation is usually random and is performed on the corresponding genotypes [See figure 1].

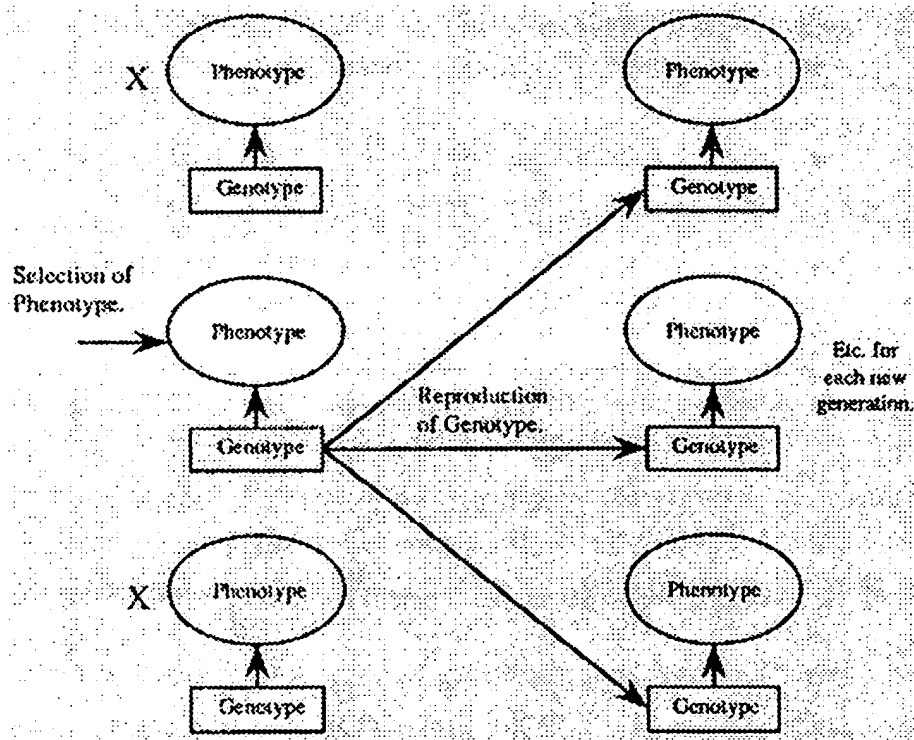


Figure 1: Phenotype selection, genotype reproduction.

The repeated cycle of reproduction with variation and selection of the most fit individuals drives the evolution of a population towards higher and higher levels of fitness.

*Sexual combination* can allow genetic material of more than one parent to be mixed together in some way to create new genotypes. This permits features to evolve independently and later be combined into a single individual. Although it is not necessary for evolution to occur, it is a valuable practice that can enhance progress in both biological and simulated evolutions.

## 2.2 Genetic Algorithms

Genetic algorithms were first developed by Holland [11] as robust searching techniques in which populations of test points are evolved by random variation and selection. They have become widely used in a number of applications to find optima in very large search spaces [23][7][6].

Genetic algorithms differ from the examples presented in this paper in that they usually utilize an explicit analytic function to measure the fitness of phenotypes. Since it is difficult to automatically measure the aesthetic visual success of simulated objects or images, here the fitness is provided by a human user based on visual perception. Some combinations of automatic selection and interactive selection are also utilized.

Population sizes used for genetic algorithms are usually fairly large (100 to 1000 or more) to allow searching of many test points and avoiding only local optima. At each generation, many individuals survive and reproduce to create the next generation. For the examples presented in this paper, the success of a solution is dependent on human opinion, therefore there is no single global optimum. Many local optima are potentially interesting solutions. For this reason, and also because of user interface practicality, a smaller population size has been used (20 - 40), and only one or two individuals are chosen to reproduce for each new generation.

Genotypes used in genetic algorithms traditionally consist of fixed-length character strings used by fixed expression rules. This is appropriate for searching predefined dimensional spaces for optimum solutions, but these restrictions are sometimes limiting. Koza [13][12] has used hierarchical lisp expressions as genotypes such that the dimensionality of the search space itself can be extended to successfully solve problems such as artificial ant navigation and game strategies. Discovery systems, such as AM, Eurisko, and Cyrano, also utilize a form of mutating lisp programs [14][8]. The examples of evolving images, volume textures, and animations presented here also use genotypic representations composed of lisp expressions, although the set of functions used includes various vector transformations, noise generators, and image processing operations, as well as standard numerical functions.

In the next section, techniques for using artificial evolution to explore samples in parameter spaces are discussed. In section 4, examples of evolving images, volume textures, and animations which utilize mutating symbolic expressions as genotypes are presented. Finally, results, suggestions for future work, and conclusions are given in the last three sections.

### **3 EXPLORING PARAMETER SPACES**

Procedural models such as fractals, graftals, and procedural texturing allow a user to create a high degree of complexity with relatively simple input information [25][21][19][18]. One method of procedural structure creation involves a set of N input parameters each of which has an effect on a developmental process which assembles the structure. The set of possible structures corresponds to the N-dimensional space of possible parameter values. Consider an array of knobs, each controlling one parameter, that can be experimentally turned to adjust the results. As more options are added to the procedure for more variation of results, the number of input parameters grows and it can become increasingly difficult for a user to predict the effects of adjusting particular parameters and combinations of parameters, and to adjust the knobs effectively by hand.

An alternative approach is to sample randomly in the neighborhood of a currently existing parameter set by making random alterations to a parameter or several parameters, then inspect and select the best sample or samples of those presented. This allows exploration through the parameter space in incremental arbitrary directions without requiring knowledge of the specific effects of each parameter. This is artificial evolution in which the genotype is the parameter set, and the phenotype is the resulting structure. Selection is performed by the user picking preferred phenotypes from groups of samples, and as long as the samples can be generated and displayed quickly enough, it can be a useful technique.

#### **3.1 Evolving 3D Plant Structures**

The first example of artificial evolution involves 3D plant structures which can be grown using a set of "genetic" parameters. Plant generation algorithms of various types have been shown to be useful examples of procedurally generated structures [29][25][22][21][16][1]. The model used in this work is described briefly below, but details have been omitted as the emphasis is on the evolutionary process.

Parameters describing fractal limits, branching factors, scaling, stochastic contributions, etc., are used to generate 3-dimensional tree structures consisting of connected segments. Growth rules use 21 genetic parameters and the hierarchy location of each segment in the tree to determine how fast that segment should grow, when it should generate new buds, and in which directions. The tree structures are grown in arbitrarily small increments for smooth simulation of development.

After a desirable tree structure has been evolved using interactive selection and the mutation methods described below, its phenotype can be saved for further manipulation. Solid polygonal branches can be generated with connected cylinders and cone shapes, and leaves can be generated by connecting sets of peripheral nodes with polygonal surfaces.

Shading parameters, color, and bump textures can be assigned to make bark and leaf surfaces. These additional properties could also be selected and adjusted using artificial evolution, but due to the longer computation times involved to test samples, these parameters were adjusted by hand. In some cases, leaf shapes were evolved independently and then explicitly added to the tip segments of other evolved plant structures. A forest of plant structures created using these methods is shown in figure 3.

### 3.2 Mutating Parameter Sets

For artificial evolution of parameter sets to occur, they must be reproduced with some probability of mutation. There are many possible methods for mutating parameter sets. The technique used here involves normalizing each parameter for a genetic value between .0 and 1.0, and then copying each genetic value or gene,  $g_i$ , from the parent to the child with a certain probability of mutation,  $m$ . A mutation is achieved by adding a random amount,  $\pm d$ , to the gene. So, a new genotype,  $G'$ , is created using each gene,  $g_i$ , of a parent genotype,  $G$ , as follows:

```
For each  $g_i$ 
  If  $\text{rand}(.0, 1.0) < m$ 
    then  $g'_i = g_i + \text{rand}(-d, d)$ 
        clamp or wrap  $g'_i$  to legal bounds.
    else  $g'_i = g_i$ 
```

The normalized values are scaled, offset, and optionally squared to give the parameter values actually used. This allows the mutation distances,  $\pm d$ , to be proportional to the scale of the range of valid parameter values. Squaring or raising some values to even higher powers can be useful because it causes more sensitivity in the lower region of the range of parameter values. The mutation rate and amount are easily adjusted, but are commonly useful at much higher values than in natural systems ( $m=0.2$ ,  $d=0.4$ ). The random value between  $-d$  and  $d$  might preferably be found using a Gaussian distribution instead of this simple linear distribution, giving smaller mutations more likelihood than larger ones.

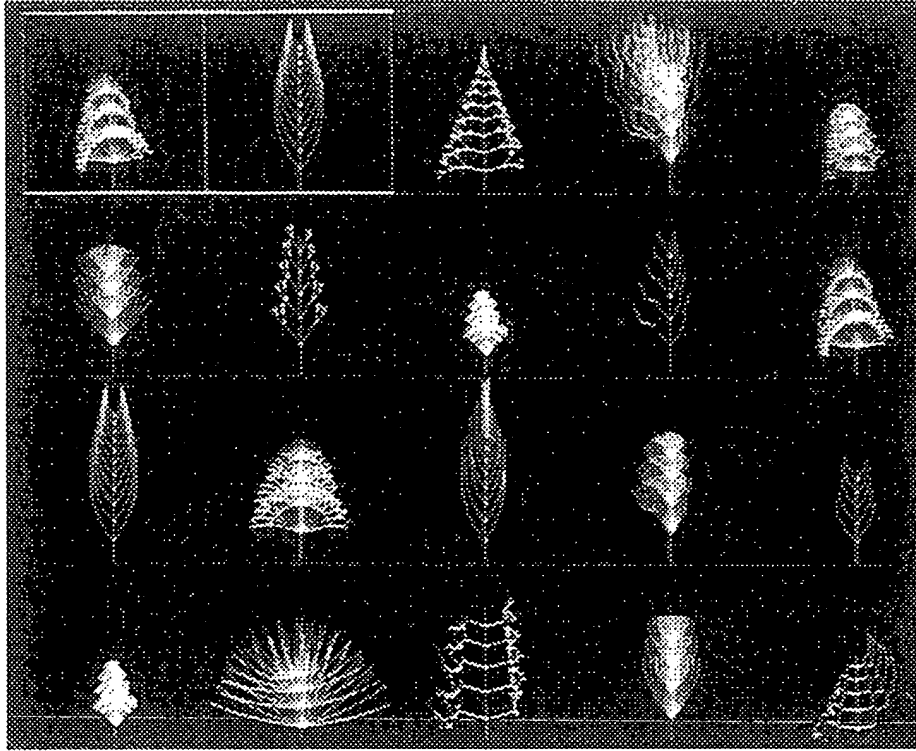
### 3.3 Mating Parameter Sets

When two parameter sets are found that both create structures with different successful features, it is sometimes desirable to combine these features into a single structure. This can be accomplished by mating them. Reproducing two parameter sets with sexual combination can be performed in many ways. Four possible methods are listed below with some of their resulting effects:

1. *Crossovers* can be performed by sequentially copying genes from one parent, but with some frequency the source genotype is switched to the other parent. This causes adjacent genes to be more likely to stick together than genes at opposite ends of the sequence. Each pair of genes has a *linkage* probability depending on their distance from each other.
2. Each gene can be independently copied from one parent or the other with equal probability. If the parent genes each correspond to a point in N-dimensional genetic space, then the genes of the possible children using this method correspond to the  $2^N$  corners of the N-dimensional rectangular solid connecting the two parent points. This method is the most commonly used in this work and is demonstrated in figure 2. Two parent plant structures are shown in the upper left boxes, and the remaining forms are their children.
3. Each gene can receive a random percentage,  $p$ , of one parent's genes, and a  $1 - p$  percentage of the other parent's genes. If the percentage is the same for each gene, linear *interpolation* between the parent genotypes results, and the children will fall randomly on the line between the N-dimensional points of the parents. If evenly spaced samples along this line were generated, a *genetic dissolve* could be made that would cause a smooth transition between the parent phenotypes if the changing parameters had continuous effects on the phenotypes. This is an example of utilizing the underlying genetic representation for specific manipulation of the results. Interpolation could also be performed with three parents to create children that fall on a triangular region of a plane in the N-dimensional genetic space.
4. Finally, each new gene can receive a random value between the two parent values of that gene. This is like the

interpolation scheme above, except each gene is independently interpolated between the parent genes. This method results in possible children anywhere within the N-dimensional rectangular solid connecting the parent points.

Mutating and mating parameter sets allow a user to explore and combine samples in a given parameter space. In the next section, methods are presented that allow mutations to add new parameters and extend the space, instead of simply adjusting existing parameter values.



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Figure 2: Mating plant structures.

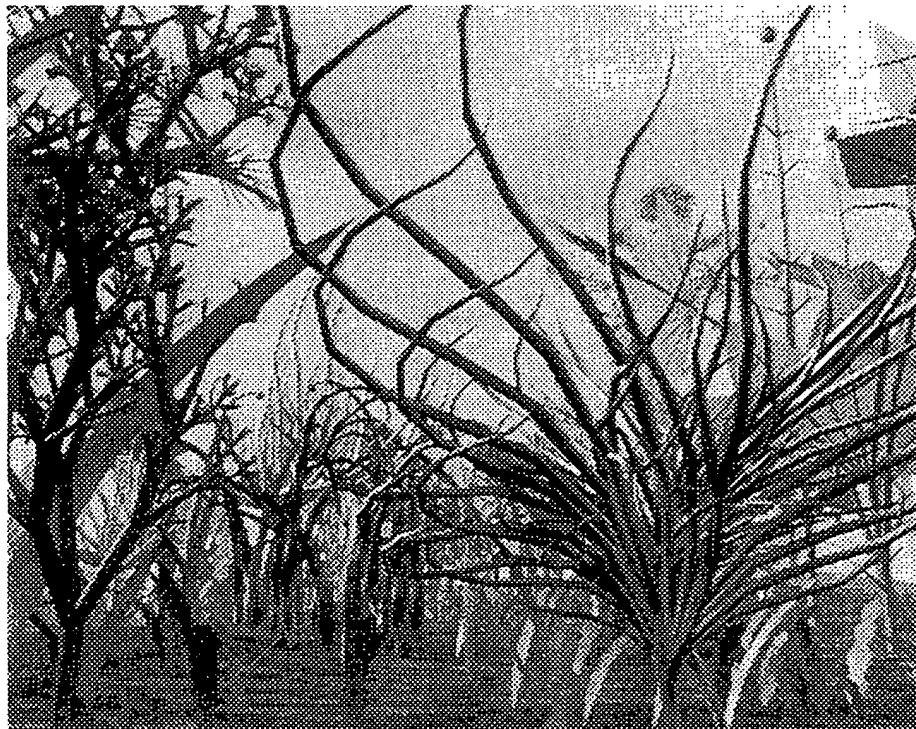


Figure 3: Forest of "evolved" plants.

#### 4 SYMBOLIC EXPRESSIONS AS GENOTYPES

A limitation of genotypes consisting of a fixed number of parameters and fixed expression rules as described above is that there are solid boundaries on the set of possible phenotypes. There is no possibility for the evolution of a new developmental rule or a new parameter. There is no way for the genetic space to be extended beyond its original definition - the N-dimensional genetic space will remain only N-dimensional.

To surpass this limitation, it is desirable to include procedural information in the genotype instead of just parameter data, and the procedural and data elements of the genotype should not be restricted to a specific structure or size.

Symbolic lisp expressions are used as genotypes in an attempt to meet these needs. A set of lisp functions and a set of argument generators are used to create arbitrary expressions which can be mutated, evolved, and evaluated to generate phenotypes. Some mutations can create larger expressions with new parameters and extend the space of possible phenotypes, while others just adjust existing parts of the expression. Details of this process are best described by the examples below.

## 4.1 Evolving Images

The second example of artificial evolution involves the generation of textures by mutating symbolic expressions. Equations that calculate a color for each pixel coordinate  $(x,y)$  are evolved using a *function set* containing some standard common lisp functions [26], vector transformations, procedural noise generators, and image processing operations:

```
+, -, *, /, mod, round, min, max, abs, expt, log, and,  
or, xor, sin, cos, atan, if, dissolve, hsv-to-rgb, vector,  
transform-vector, bw-noise, color-noise, warped-bw-noise,  
warped-color-noise, blur, band-pass, grad-mag, grad-dir,  
bump, ifs, warped-ifs, warp-abs, warp-rel, warp-by-grad.
```

Each function takes a specified number of arguments and calculates and returns an image of scalar (b/w) or vector (color) values.

Noise generators can create solid 2D scalar and vector noise at various frequencies with random seeds passed as arguments so specific patterns can be preserved between generations [figure 4f, and 4i]. The warped versions of functions take  $(U,V)$  coordinates as arguments instead of using global  $(X,Y)$  pixel coordinates, allowing the result to be distorted by an arbitrary inverse mapping function [figure 4i]. Boolean operations (*and*, *or*, and *xor*) operate on each bit of floating-point numbers and can cause fractal-like grid patterns [figure 4e]. Versions of *sin* and *cos* which normalize their results between .0 and 1.0 instead of -1.0 and 1.0 can be useful. Some functions such as blurs, convolutions, and those that use gradients also use neighboring pixel values to calculate their result [figure 4h]. *Band-pass* convolutions can be performed using a difference of Gaussians filter which can enhance edges. Iterative function systems (*ifs*) can generate fractal patterns and shapes.



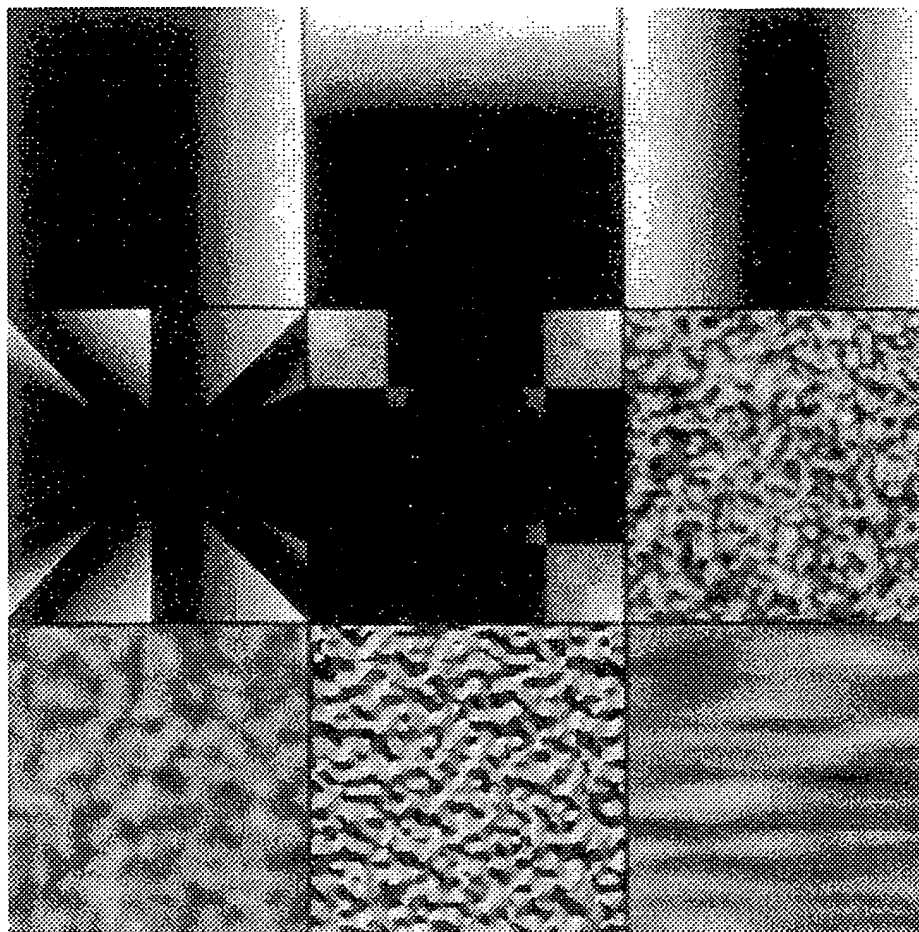


Figure 4: Simple expression examples.

(reading left to right, top to bottom)

- a.  $X$
- b.  $Y$
- c.  $(abs\ X)$
- d.  $(mod\ X\ (abs\ Y))$
- e.  $(and\ X\ Y)$
- f.  $(bw-noise\ .2\ 2)$
- g.  $(color-noise\ .1\ 2)$
- h.  $(grad-direction\ (bw-noise\ .15\ 2)\ .0\ .0)$
- i.  $(warped-color-noise\ (*\ X\ .2)\ Y\ .1\ 2)$

Details of the specific implementations of these functions are not given here because they are not as important as the methods used for combining them into longer expressions. Many other functions would be interesting to include in this *function set*, but these have provided for a fairly wide variety of resulting images.

Simple random expressions are generated by choosing a function at random from the *function set* above, and then generating as many random arguments as that function requires. Arguments to these functions can be either scalars or vectors, and either constant values or images of values. Random arguments can be generated from the following forms:

- A random scalar value such as  $.4$
- A random 3-element vector such as  $\#(.42\ .23\ .69)$
- A variable such as the  $X$  or  $Y$  pixel coordinates.
- Another lisp expression which returns a b/w or color image.

Most of the functions have been adapted to either coerce the arguments into the required types, or perform differently according to the argument types given to them. Arguments to certain functions can optionally be restricted to some subset of the available types. For the most part these functions receive and return images, and can be considered as image processing operations. Expressions are simply evaluated to produce images. Figure 4 shows examples of some simple expressions and their resulting images.

Artificial evolution of these expressions is performed by first generating and displaying a population of simple random expressions in a grid for interactive selection. The expressions of images selected by the user are reproduced with mutations, for each new generation such that more and more complex expressions and more perceptually successful images can evolve. Some images evolved with this process are shown in figures 9 to 13.

## 4.2 Mutating Symbolic Expressions

Symbolic expressions must be reproduced with mutations for evolution of them to occur. There are several properties of symbolic expression mutation that are desirable. Expressions should often be only slightly modified, but sometimes significantly adjusted in structure and size. Large random changes in genotype usually result in large jumps in phenotype which are less likely to be improvements, but are necessary for extending the expression to more complex forms.

A recursive mutation scheme is used to mutate expressions. Lisp expressions are traversed as tree structures and each node is in turn subject to possible mutations. Each type of mutation occurs at different frequencies depending on the type of node:

1. Any node can mutate into a new random expression. This allows for large changes, and usually results in a fairly significant alteration of the phenotype.
2. If the node is a scalar value, it can be adjusted by the addition of some random amount.
3. If the node is a vector, it can be adjusted by adding random amounts to each element.
4. If the node is a function, it can mutate into a different function. For example  $(abs\ X)$  might become  $(cos\ X)$ . If this mutation occurs, the arguments of the function are also adjusted if necessary to the correct number and types.
5. An expression can become the argument to a new random function. Other arguments are generated at random if necessary. For example  $X$  might become  $(*\ X\ .3)$ .
6. An argument to a function can jump out and become the new value for that node. For example  $(*\ X\ .3)$  might become  $X$ . This is the inverse of the previous type of mutation.
7. Finally, a node can become a copy of another node from the parent expression. For example  $(+\ (abs\ X)\ (*\ Y\ .6))$  might become  $(+\ (abs\ (*\ Y\ .6))\ (*\ Y\ .6))$ . This causes effects similar to those caused by mating an expression with itself. It allows for sub-expressions to duplicate themselves within the overall expression.

Other types of mutations could certainly be implemented, but these are sufficient for a reasonable balance of slight modifications and potential for changes in complexity.

It is preferable to adjust the mutation frequencies such that a decrease in complexity is slightly more probable than an increase. This prevents the expressions from drifting towards large and slow forms without necessarily improving the results. They should still easily evolve towards larger sizes, but a larger size should be due to selection of improvements instead of random mutations with no effect.

The relative frequencies for each type of mutation above can be adjusted and experimented with. The overall mutation frequency is scaled inversely in proportion to the length of the parent expression. This decreases the probability of mutation at each node when the parent expression is large so that some stability of the phenotypes is maintained.

The evaluation of expressions and display of the resulting images can require significant calculation times as expressions increase in complexity. To keep image evolution at interactive speeds, estimates of compute speeds are calculated for each expression by summing pre-computed runtime averages for each function. Slow expressions are eliminated before ever being displayed to the user. New offspring with random mutations are generated and tested until fast enough expressions result. In this way automatic selection is combined with interactive selection. If necessary, this technique could also be performed to keep memory usage to a minimum.

### 4.3 Mating Symbolic Expressions

Symbolic expressions can be reproduced with sexual combinations to allow sub-expressions from separately evolved individuals to be mixed into a single individual. Two methods for mating symbolic expressions are described.

The first method requires the two parents to be somewhat similar in structure. The nodes in the expression trees of both parents are simultaneously traversed and copied to make the new expression. When a difference is encountered between the parents, one of the two versions is copied with equal probability. For example, the following two parents can be mated to generate four different expressions, two of which are equal to the parents, and two of which have some portions from each parent:

```
parent1: (* (abs X) (mod X Y))
parent2: (* (/ Y X) (* X -.7))

child1: (* (abs X) (mod X Y))
child2: (* (abs X) (* X -.7))
child3: (* (/ Y X) (mod X Y))
child4: (* (/ Y X) (* X -.7))
```

This method is often useful for combining similar expressions that each have some desired property. It usually generates offspring without very large variations from the parents. Two expressions with different root nodes will not form any new combinations. This might be compared to the inability of two different species to mate and create viable offspring.

The second method for mating expressions combines the parents in a less constrained way. A node in the expression tree of one parent is chosen at random and replaced by a node chosen at random from the other parent. This *crossing over* technique allows any part of the structure of one parent to be inserted into any part of the other parent and permits parts of even dissimilar expressions to be combined. With this method, the parent expressions above can generate 61 different child expressions - many more than the 4 of the first method.

### 4.4 Evolving Volume Textures

A third variable,  $Z$ , is added to the list of available arguments to enable functions to be evolved that calculate colors for each point in  $(X, Y, Z)$  space. The *function set* shown in section 4.1 is adjusted for better results: 2D functions that require neighboring pixel values such as convolutions and warps are removed, and 3D solid noise generating functions are added.

These expressions are more difficult to visualize because they encompass all of 3D space. They are evaluated on the surfaces of spheres and planes for fast previewing and selection as shown in figure 5. Evolved volume expressions can then be incorporated into procedural shading functions to texture arbitrary objects. This process allows complex volume textures such as those described in [18] and [19] to be evolved without requiring specific equations to be understood and carefully adjusted by hand. Figure 6 was generated by evolving three volume texture expressions and then evaluating them at the surfaces positions of three objects during the rendering process.

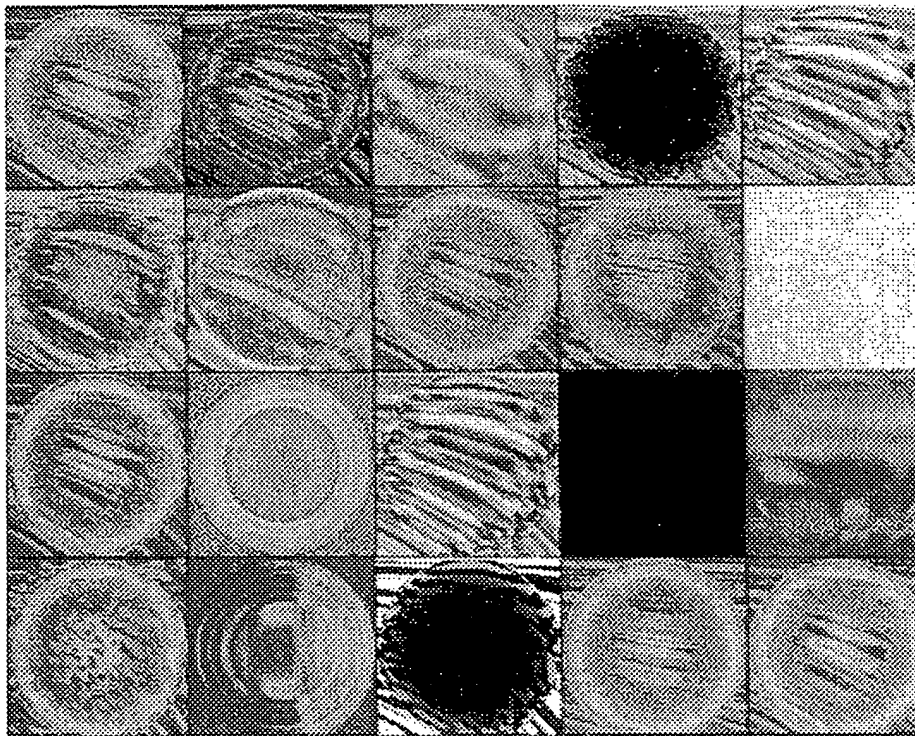


Figure 5: Parent with 19 random mutations.

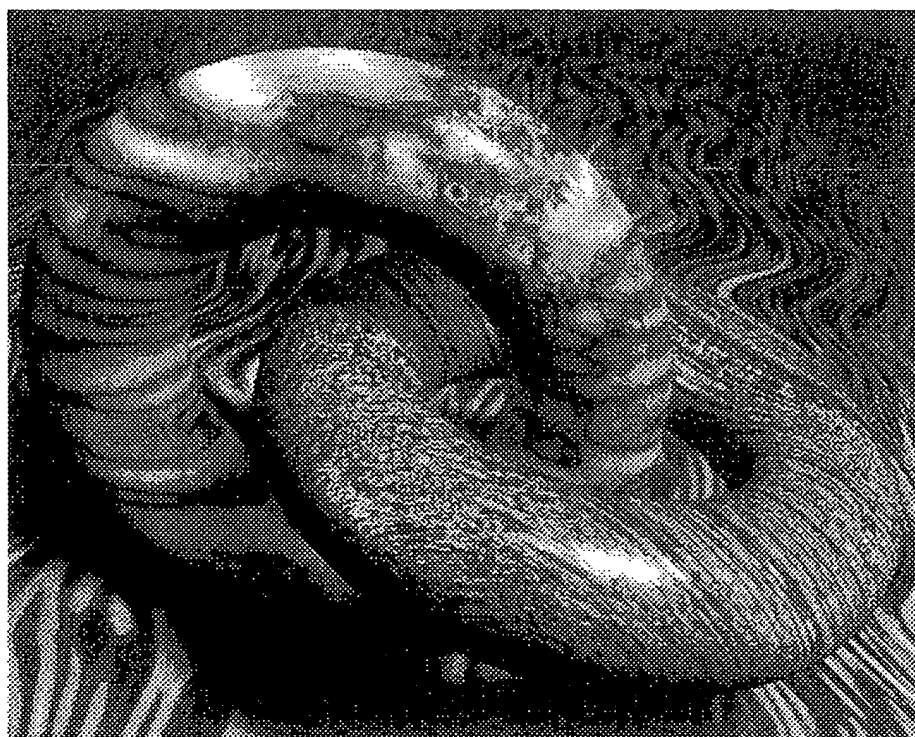


Figure 6: Marble and wooden tori.

## 4.5 Evolving Animations

Several extensions to the image evolution system described above can be used to evolve moving images. Five methods for incorporating a temporal dimension in symbolic expressions are proposed:

1. Another input variable, *Time*, can be added to the list of available arguments. Expressions can be evolved that are functions of  $X, Y$ , and *Time* such that different images are produced as the value of *Time* is smoothly animated. More computation is required to generate, display and select samples because a sequence of images must be calculated. An alternate method of display involves displaying various slices of the  $(X, Y, Time)$  space (although

operations requiring neighboring pixel values might not receive the correct information if the values of *Time* vary between them).

2. *Genetic cross dissolves* can be performed between two expressions of similar structure. Interpolation between two expressions is performed by matching the expressions where they are identical and interpolating between the results where they are different. Results of differing expression branches are first calculated and dissolved, and then used by the remaining parts of the expression. If the two expressions have different root nodes, a conventional image dissolve will result. If only parts within their structures are different, interesting motions can occur. This technique utilizes the existing genetic representation of evolved still images to generate in-betweens for a smooth transition from one to another. It is an example of the usefulness of the alternate level of control given by the underlying genetic information. A series of frames from a genetic cross dissolve are shown in figure 7.

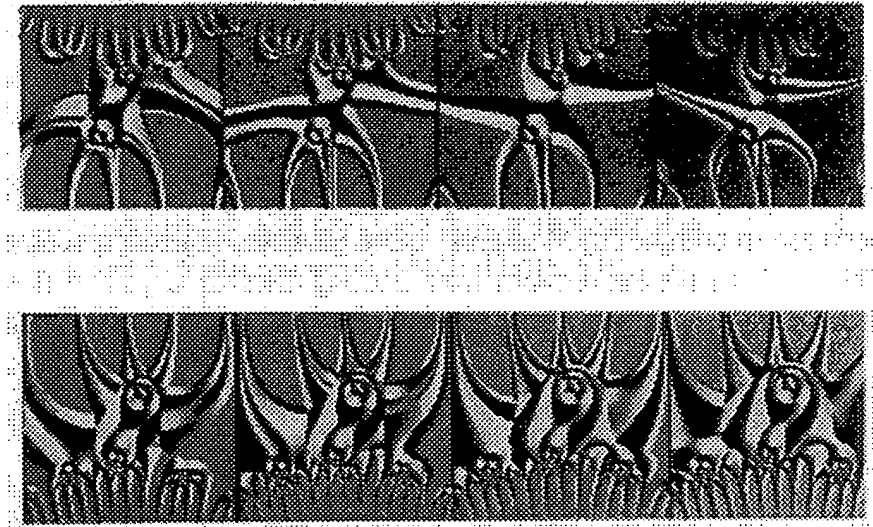
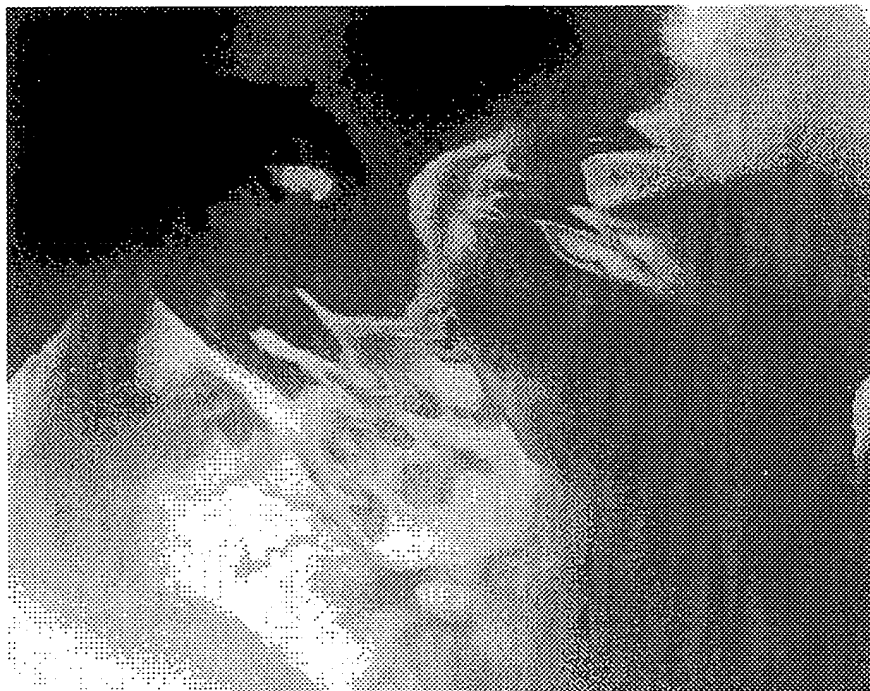


Figure 7: Frames from a "genetic cross dissolve."

3. An input image can be added to the list of available arguments to make functions of *X*, *Y*, and *Image*. The input image can then be animated and processed by evaluating the expression multiple times for values of *Image* corresponding to frames of another source of animation such as hand drawn or traditional 3D computer graphics. This is effectively a technique for evolving complex image processing and warping functions that compute new images from given input images. Figure 8 was created in this way with an input image of a human face.



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Figure 8: Fire of Faces.

4. The images that use the pixel coordinates  $(X,Y)$  to determine the colors at each pixel can be animated by altering the mappings of  $X$  and  $Y$  before the expression is evaluated. Simple zooming and panning can be performed as well as 3D perspective transformations and arbitrary patterns of distortion.
5. Evolved expressions can be adjusted and experimented with by hand. If parameters in expressions are smoothly interpolated to new values, the corresponding image will change in potentially interesting ways. For example, solid noise can be made to change frequency, colors can be dissolved into new shades, and angles can be rotated. This is another example of utilizing the underlying genetic information to manipulate images. A small change in the expression can result in a powerful alteration of the resulting image.

Finally, the techniques above can be used together in various combinations to make an even wider range of possibilities for evolving animations.

## 5 RESULTS

Evolution of 3D plant structures, images, solid textures, and animations have been implemented on the Connection Machine<sup>(R)</sup> system CM-2, a data parallel supercomputer [27][10]. The parallel implementation details will not be discussed in this paper, but each application is reasonably suited for highly parallel representation and computation. Lisp expression mutations and combinations are performed on a *front-end* computer and the Connection Machine system is used to evaluate the expression for all pixels in parallel using *Starlisp* and display the resulting image.

3D Plant structures have been evolved and used in the animated short *Panspermia* [24]. A frame from this sequence is shown in figure 3 which contains a variety of species created using these techniques. An interactive system for quickly growing, displaying, and selecting sample structures allows a wide range of plant shapes to be efficiently created by artificial evolution. Populations of samples can be displayed for selection in wire frame in a grid format as shown in figure 2, or displayed as separate higher-resolution images which can be interactively flipped through by scrolling with a mouse. Typically between 5 and 20 generations are necessary for acceptable structures to emerge.

Images, volume textures, and various animations have been created using mutating symbolic expressions. These sometimes require more generations to evolve complex expressions that give interesting images - often at least 10 to 40 generations. Again, an interactive tool for quickly displaying grids of sample images to be selected amongst makes the evolution process reasonably efficient. [See figure 5.] The number of possible symbolic expressions of acceptable length is extremely large, and a wide variety of textures and patterns can occur. Completely unexpected kinds of images have emerged. Figure 9 was created from the following evolved expression:

```
(round (log (+ y (color-grad (round (+ (abs (round
(log (+ y (color-grad (round (+ y (log (invert y) 15.5))
x) 3.1 1.86 #(0.95 0.7 0.59) 1.35)) 0.19) x)) (log (invert
y) 15.5)) x) 3.1 1.9 #(0.95 0.7 0.35) 1.35)) 0.19) x)
```



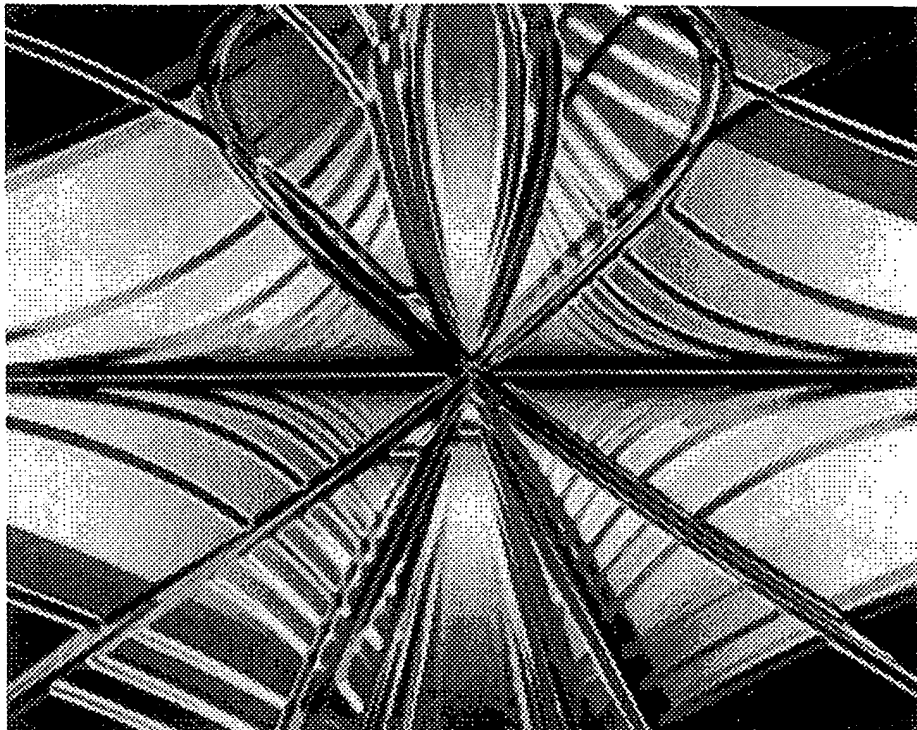


Figure 9

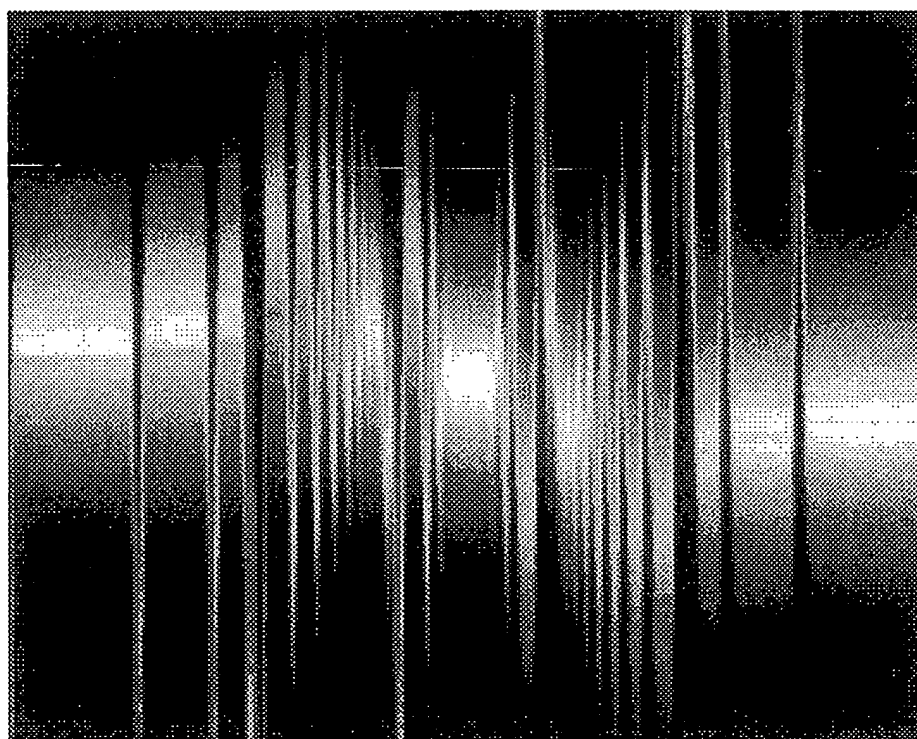


Figure 10



Figure 11

Figure 13 was created from this expression:

```
(sin (+ (- (grad-direction (blur (if (hsv-to-rgb (warped-
color-noise #(0.57 0.73 0.92) (/ 1.85 (warped-color-
noise x y 0.02 3.08)) 0.11 2.4)) #(0.54 0.73 0.59) #(1.06
0.82 0.06)) 3.1) 1.46 5.9) (hsv-to-rgb (warped-color-
noise y (/ 4.5 (warped-color-noise y (/ x y) 2.4 2.4))
0.02 2.4))) x))
```

Note that expressions only five or six lines long can generate images of fair complexity. Equations such as these can be evolved from scratch in timescales of only several minutes - probably much faster than they could be designed.

Figures 10, 11, and 12 were also created from expressions of similar lengths. Fortunately, analysis of expressions is not required when using these methods to create them. Users usually stop attempting to understand why each expression generates each image. However, for those interested, expressions for other figures are listed in the appendix.

Two different approaches of user selection behavior are possible. The user can have a goal in mind and select samples that are closer to that goal until it is hopefully reached. Alternatively, the user can follow the more interesting samples as they occur without attempting to reach any specific goal.

The results of these various types of evolved expressions can be saved in the very concise form of the final genotypic expression itself. This facilitates keeping large libraries of evolved forms which can then be used to contribute to further evolutions by mating them with other forms or further evolving them in new directions.



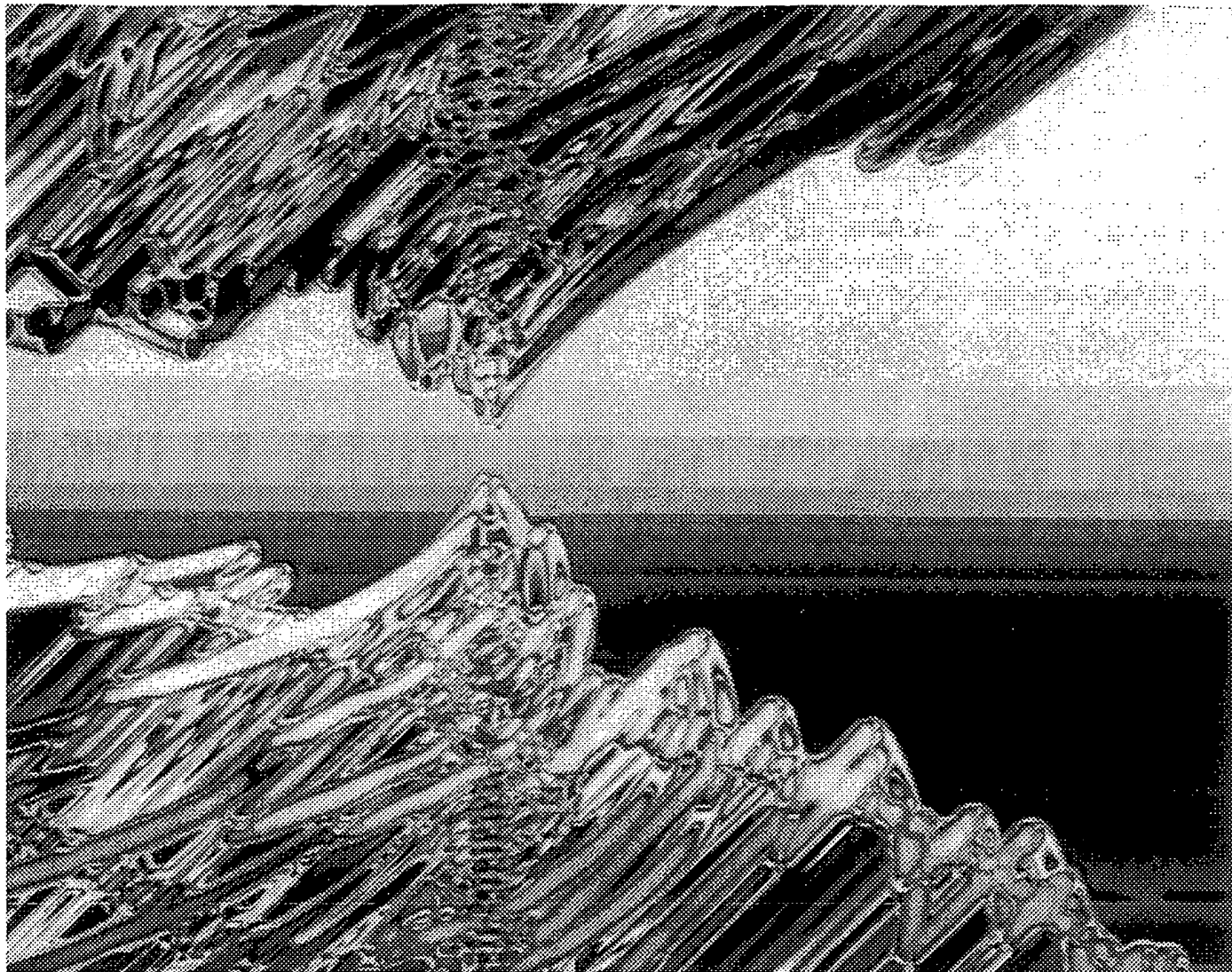


Figure 12

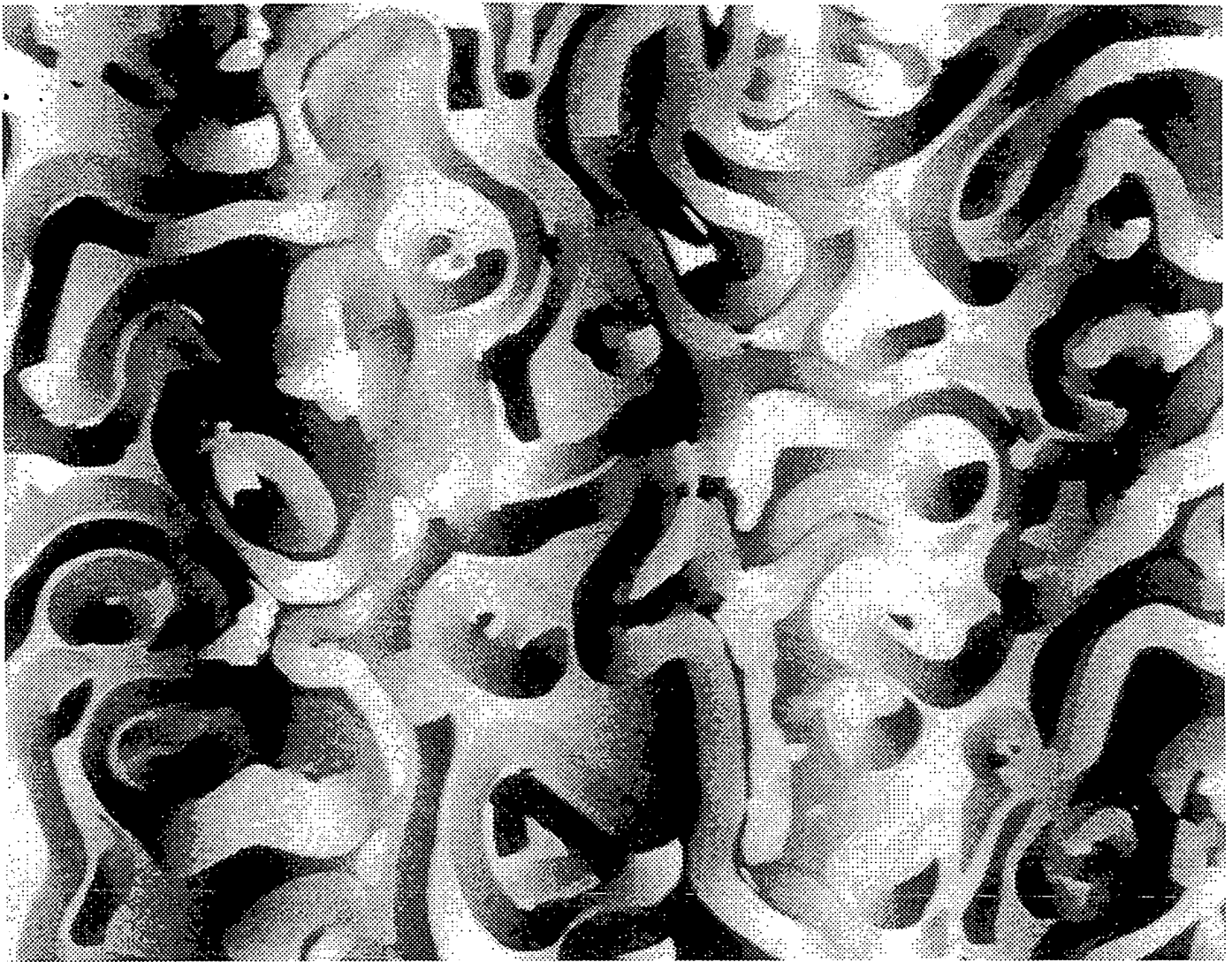


Figure 13

## 6 FUTURE WORK

Artificial evolution has many other possible applications for computer graphics and animation. Procedures that use various other forms of solid noise could be explored, such as those that create objects, create density functions, or warp objects [15][20]. Procedures could be evolved that generate motion from a set of rules (possibly cellular automata, or particle systems), or that control distributions and characteristics of 2D objects such as lines, solid shapes, or brush strokes. Algorithms that use procedural construction rules to create 3D objects from polygons, or functions that generate, manipulate, and combine geometric primitives could also be explored.

These techniques might also make valuable tools in domains beyond computer simulations. New possibilities for shapes and textures could be explored for use in product design or the fashion industry.

Several variations on the methods for artificial evolution described above might make interesting experiments. Mutation frequencies could be included in the genotype itself so that they also can be mutated. This might allow for the evolution of evolvability [4]. Frequencies from the most successful evolutions could be kept as the defaults.

It might be interesting to attempt to automatically evolve a symbolic expression that could generate a simple specific goal image. An image differencing function could be used to calculate a *fitness* based on how close a test image was to the goal, and an expression could be searched for by automatic selection. Then, interactive selection could be used to evolve further images starting with that expression.

Large amounts of information of all the human selection choices of many evolutions could be saved and analyzed. A difficult challenge would be to create a system that could generalize and "understand" what makes an image visually

successful, and even generate other images that meet these learned criteria.

Combinations of random variations and non-random variations using learned information might be helpful. If a user picks phenotypes in a certain direction from the parent, mutations for the next generation might have a tendency to continue in that same direction, causing evolution to have "momentum."

Also, combinations of evolution and the ability to apply specific adjustments to the genotype might allow more user control over evolved results. Automatic "genetic engineering" could permit a user to request an evolved image to be more blue, or a texture more grainy.

## 7 CONCLUSION

Artificial evolution has been demonstrated to be a potentially powerful tool for the creation of procedurally generated structures, textures, and motions. Reproduction with random variations and survival of the visually interesting can lead to useful results. Representations for genotypes which are not limited to fixed spaces and can grow in complexity have shown to be worthwhile.

Evolution is a method for creating and exploring complexity that does not require human understanding of the specific process involved. This process of artificial evolution could be considered as a system for helping the user with creative explorations, or it might be considered as a system which attempts to "learn" about human aesthetics from the user. In either case, it allows the user and computer to interactively work together in a new way to produce results that neither could easily produce alone.

An important limiting factor in the usefulness of artificial evolution is that samples need to be generated quickly enough such that it is advantageous for the user to choose from random samples instead of carefully adjusting new samples by hand. The computer needs to generate and display samples fast enough to keep the user interested while selecting amongst them. As computation becomes more powerful and available, artificial evolution will hopefully become advantageous in more and more domains.

## 8 Acknowledgments

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## APPENDIX

Figure 5, Parent expression:

*(warped-color-noise (warped-bw-noise (dissolve x 2.53 y) z 0.09 12.0) (invert z) 0.05 -2.06).*

Figure 6, Marble torus:

*(dissolve (cos (and 0.25 #(0.43 0.73 0.74))) (log (+ (warped-bw-noise (min z 11.1) (log (rotate-vector (+ (warped-bw-noise (cos x) (dissolve (cos (and 0.25 #(0.43 0.73 0.74))) (log (+ (warped-bw-noise (max (min z 8.26) (/ -0.5 #(0.82 0.39 0.19))) (log (+ (warped-bw-noise (cos x) z -0.04 0.89) #(0.82 0.39 0.19)) #(0.15 0.34 0.50)) -0.04 -3.0) y) #(0.15 0.34 0.50)) y) -0.04 -3.0) x) z y) #(0.15 0.34 0.5)) -0.02 -1.79) -0.4) #(-0.09 0.34 0.55)) -0.7)*

Figure 7, Cross dissolve:

*(hsv-to-rgb (bump (hsv-to-rgb (ifs 2.29 0.003 (dissolve 1.77 3.67 time) 2.6 0.1 (dissolve 5.2 3.2 time) -31.0 (dissolve 23.9 -7.4 time) (dissolve 1.13 9.5 time) (dissolve 4.8 0.16 time) 20.7 4.05 (dissolve 0.48 0.46 time) (dissolve 2.94 -0.68 time) (dissolve 0.42 0.54 time) (dissolve 0.09 0.54 time)))) (atan 2.25 (dissolve 0.1 0.11 time) 0.15) (dissolve 4.09 8.23 time) (dissolve #(0.41 0.36 0.08) #(0.68 0.22 0.31) time) #(0.36 0.31 0.91) (dissolve 6.2 4.3 time) (dissolve 0.16 0.40 time) (dissolve 2.08 0.23 time)))*

Figure 8, Fire of Faces:

```
(+ (min 10.8 (warp-rel image image (bump image x 9.6 #(0.57 0.02 0.15) #(0.52 0.03 0.38) 3.21 2.49 10.8))) (dissolve  
#(0.81 0.4 0.16) x (dissolve y #(0.88 0.99 0.66) image)))
```

Figure 10:

```
(rotate-vector (log (+ y (color-grad (round (+ (abs (round (log #(0.01 0.67 0.86) 0.19) x)) (hsv-to-rgb (bump (if x 10.7  
y) #(0.94 0.01 0.4) 0.78 #(0.18 0.28 0.58) #(0.4 0.92 0.58) 10.6 0.23 0.91))) x) 3.1 1.93 #(0.95 0.7 0.35) 3.03)) -0.03) x  
#(0.76 0.08 0.24))
```

Figure 11 is unfortunately "extinct" because it was created before the genome saving utility was complete.

Figure 12:

```
(cos (round (atan (log (invert y) (+ (bump (+ (round x y) y) #(0.46 0.82 0.65) 0.02 #(0.1 0.06 0.1) #(0.99 0.06 0.41)  
1.47 8.7 3.7) (color-grad (round (+ y y) (log (invert x) (+ (invert y) (round (+ y x) (bump (warped-ifs (round y y) y 0.08  
0.06 7.4 1.65 6.1 0.54 3.1 0.26 0.73 15.8 5.7 8.9 0.49 7.2 15.6 0.98) #(0.46 0.82 0.65) 0.02 #(0.1 0.06 0.1) #(0.99 0.06  
0.41) 0.83 8.7 2.6)))))) 3.1 6.8 #(0.95 0.7 0.59) 0.57))) #(0.17 0.08 0.75) 0.37) (vector y 0.09 (cos (round y y)))))
```

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